TOWN OF BLUFFTON WETLAND POTENTIAL MAPPING

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Prepared by the Center for Watershed Protection, Inc.

CENTER FOR WATERSHED PROTECTION

and McCormick Taylor

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Prepared for the Town of Bluffton, South Carolina

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ACRONYMS & ABBREVIATIONS

Acronym/Abbreviation	Definition
CWA	Clean Water Act
CWP	Center for Watershed Protection, Inc.
GIS	Geographic Information Systems
NOAA	National Oceanic and Atmospheric Administration
NWI	National Wetlands Inventory
SCOTUS	Supreme Court of the United States
UDO	Unified Development Ordinance
USFWS	United States Fish & Wildlife Service
SC	South Carolina
UDO	Unified Development Ordinance
ASPRS	American Society for Photogrammetry and Remote Sensing
NRCS	Natural Resource Conservation Service
FGDC	Federal Geographic Data Committee
RF	Random Forest
SVM	Support Vector Machines
KNN	K Nearest Known/Neighbor
NDVI	Normalized Difference Vegetation Index
DEM	Digital Elevation Model
CNN	Convolutional Neural Networks
ML	Machine Learning
PA	Producer's Accuracy
UA	User's Accuracy
USGS	United State Geological Survey
MRLC	Multi-Resolution Land Characteristics consortium
NLCD	National Land Cover Dataset
C-CAP	Coastal Change Analysis Program
LULC	Land Use/Land Cover

INTRODUCTION

In May of 2023, the Supreme Court of the United States (SCOTUS) stripped federal oversight from millions of acres of wetlands long protected under the Clean Water Act (CWA). SCOTUS ruled that waters regulated by the CWA must have a "continuous surface connection" to lakes and rivers that affect interstate commerce. Therefore, isolated wetlands, intermittent, and ephemeral streams may not be protected as they are not "relatively permanent, standing or continuously flowing bodies of water." Erecting safeguards to ensure those waters are not polluted, drained or filled in by developers falls to the states. Absent strong wetland protections at the state level, the Town of Bluffton, SC (the Town) has since instituted a 50-ft buffer requirement in its Unified Development Ordinance (UDO) for all wetlands and is working on additional updates to require more stringent protection for high-value wetlands.

The Town currently relies on the National Wetland Inventory (NWI) produced and maintained by the U.S. Fish and Wildlife Service (USFWS), which is the primary source of mapped wetland features used across the country. However, the NWI has limitations and the USFWS cautions that the data should not be interpreted as representing the presence, absence, or extent of wetlands that may be covered under one or more federal, state, Tribal, or local laws. Within the Town, the NWI was last updated from imagery in 2006 and 2011. Areas of the Town developed after these dates are likely to have undergone changes resulting in wetland loss and areas without development may have experienced wetland change from natural processes. In addition, it typically does not include wetlands smaller than one to three acres (FGDC, 2009), ephemeral wetlands, farmed wetlands, and certain wetlands that are difficult to photointerpret (e.g., submerged aquatic vegetation, intertidal and subtidal zones of estuaries, nearshore coastal waters)[1]. In order for the Town to protect wetlands, an updated and more complete inventory of wetland locations (particularly isolated wetlands) is needed. This report summarizes the available desktop-level methods and data to supplement the NWI that the Town can use to identify wetlands within its municipal jurisdiction.

AVAILABLE METHODS AND DATA

Existing desktop-level tools and methods to identify wetlands were compiled by the Center for Watershed Protection (CWP) from online searches and resources provided by the project partners, including the Town and McCormick Taylor. Datasets required for each tool or method, and their availability for the Bluffton area, were also researched. A summary of the findings and recommendations for how the Town can broadly identify wetland areas are provided in this section. Note that this analysis only includes a review of desktop assessment methods and does not include field delineations.

Summary of Methods

The identification and delineation of wetlands can be approached using a range of GIS and remote sensing techniques, each varying in complexity, accuracy, and resource requirements. The selection of an appropriate method depends on several factors, including the size and scope of the project, the precision required, the technical expertise of the project team, and the resources available. These methods fall into broad categories that span from manual digitization to advanced deep learning models.

1. **Heads-Up Digitizing (Manual Digitization)**

[1] https://www.fws.gov/node/264582

At the most basic level, wetlands can be delineated by manually tracing them from digital imagery or high-resolution aerial photos, which is a method referred to as heads-up digitization. Users rely on visual interpretation skills and basic GIS tools to trace features directly from maps, often referencing ancillary datasets that include hydrologic indicators, vegetation patterns, or soil data. This is the foundational method used by the USFWS in creating the National Wetlands Inventory NWI (EPRI, 2019; USFWS, 2020).

This method is highly dependent on the quality of the imagery, the experience of the image analysts, the amount and quality of the ancillary data, and the amount of ground truth verification work conducted. The preferred imagery is leaf-off digital color infrared that is less than 5 years old with a resolution of 1.0 meter or less. Wetland image analysts review the imagery for basic elements of tone, size, shape, texture, pattern shadow, geographic location, and association with other objects to make decisions about ecological habitat boundaries to map wetlands. Analysts are recommended to have certification and advanced training, such as the Certified Mapping Scientists, Remote Sensing from the American Society for Photogrammetry and Remote Sensing (ASPRS) and 3 years of experience in photogrammetric and cartographic applications (USFWS, 2020).

2. **Overlay Analysis**

Overlay analysis is a geospatial modeling approach where various GIS datasets of wetland indicators, defined as "data that indicate the potential presence of wetlands," are combined to generate a probability surface of wetland occurrence. This method identifies areas with a higher probability of wetlands being present in areas where multiple wetland indicators overlap. Wetland indicators can include data on hydric soils, wetland vegetation, topography, floodplains, aerial imagery, and up to date data on existing wetland features. Identifying where the overlap occurs between known features that signify wetland presence helps the analyst to identify areas where wetlands are most likely to exist. The use of a singular dataset such as hydric soils or wetland vegetation is likely to over- or underestimate wetland presence (CWP, 2010).

Overlay analyses are flexible and can be adapted to different geographic contexts. They require a moderate level of GIS expertise and can utilize data that is publicly available from government agencies, including the U.S. Geological Survey (USGS), the U.S. Natural Resource Conservation Service (NRCS), and the USFWS. The overall accuracy of outputs from this method are directly related to the amount and quality of the input data. It is important to note that the overlay analysis method is not intended as and should not be used as a substitute for regulatory determinations or field delineations of wetlands.

3. **Machine Learning**

More advanced wetland identification techniques take advantage of the availability of high-resolution data and relatively cheap and fast computing abilities using machine learning modeling approaches. The University of California at Berkeley's School of Information has defined machine learning as a data science technique that "involves using statistical learning and optimization methods that let computers analyze datasets and identify patterns… [these techniques] leverage data mining to identify historic trends and inform future models" (UC Berkeley, 2020). Note that while machine learning and artificial intelligence (AI) are related, machine learning "specifically refers to teaching devices to learn information given to a dataset within manual human interference" (UC Berkeley, 2020). These methods leverage machine learning algorithms such as Random Forest (RF), Support Vector Machine (SVM), K-Nearest Neighbors (KNN) which can effectively classify wetlands when paired with derived features, such as the Normalized Difference Vegetation Index (NDVI) (EPRI, 2019). However, these traditional models often require extensive feature engineering and may struggle with complex, non-linear relationships in the data.

Machine learning is often used in the remote sensing field (i.e., spectral analysis of aerial and satellite imagery) and involves the identification of key spectral signatures for individual vegetation species or communities found in wetlands (Gale, 2021). It is also used with non-spectral spatial data modeling inputs, such as terrain and surface hydrology characteristics derived from DEMs, which are often less resource-intensive since the models are more generalized and capture a variety of wetland types based on geomorphologic and hydrologic signatures (Gale, 2021).

Deep learning is a subset of machine learning that can address limitations related to computational capacity and complex non-linear relationships. In particular, convolutional neural networks (CNNs) excel at image segmentation tasks and can process raw imagery with minimal preprocessing, thereby reducing the need for costly feature extraction. They are especially effective in handling complex interactions among variables, including conditionality and non-linearities in the relationships between predictor and response variables, making them well suited for mapping wetlands across large and heterogeneous landscapes (Mainali et al., 2023). Deep learning object-based approaches take into account ecologically meaningful information from the surrounding area including shape and texture and avoids the "salt and pepper" outcomes of other machine learning pixel-based approaches. These models are ideal for high-resolution applications and can outperform traditional machine learning models when sufficient training data is available (EPRI, 2019).

Machine learning approaches are constrained by the extent of available ground truth data and the computational burden associated with large datasets. Test data sets for machine learning are used to measure the generality – a model's ability to perform well on new unseen data beyond the training data set – of the machine learning model. While it is imperative that sufficient data is available to train a machine learning model, it may be a challenge to determine how much data is needed until after the model-building process has begun. With limited data availability, the complexity of the machine learning model will need to be limited. In these cases, less is more when it comes to the selection of parameters for the machine learning model (Lones, 2024). According to the California Learning Resource Network[2], the amount of training data needed varies widely from at least ten events for every predictor (e.g., 10 features for each feature type you want to map) for logistic regression models to millions of examples for deep learning models.

An appropriate test dataset should not overlap with the training dataset for the machine learning model and should be representative of the wider population under study. The model's training and testing must occur within the spatial boundaries of the ground truth dataset. Therefore, when considering Town-wide applications, the training dataset must encompass the full extent of the town to ensure the model's reliability. The computational burden can be mitigated by using cloud computing platforms, such as Google Cloud Platform, Microsoft Azure, and open platforms like Google Earth Engine and Microsoft's Planetary Computer. These platforms enable the efficient processing, storage, and analysis of vast remote sensing datasets (Mainali et al., 2023).

Table 1 provides a summary of nine wetland identification case studies that use the overlay analysis and machine learning methods. For each case study, the accuracy is presented as both a user's and producer's

[2] How much data is needed for machine learning? - California Learning Resource Network

accuracy[3] when provided by the study documentation. Producer's accuracy (PA) is from the point of view of the map maker and represents the probability that a wetland on the ground will be included on the map. It is also referred to as a Type 2 error and identifies false negatives, or errors of omission. In comparison, user's accuracy (UA) is from the point of view of the map user and represents the probability that a wetland on the map will actually be present on the ground. It is also referred to as a Type 1 error and shows false positives, or errors of commission.

The level of effort associated with the case study methods is also categorized as high, medium, or low according to the following:

- Low – Method is ready to use without modification and will require 1-2 days of staff time
- Medium – Method is ready to use with limited modifications and will require 1-2 weeks of staff time
- High – Method will require complete development or significant modification and more than 2 weeks of staff time

Table 1. Summary of wetland identification case studies

Method	**Source**	**Method Type**	**Location**	**Accuracy***	**Level of Effort**	**Limitations**
Wetlands-At-Risk Protection Tool	CWP	Overlay Analysis	Frederick County, MD	UA: 23%	Low	The quality and limitation associated with the input data will directly affect the accuracy of the results.
Southeast Isolated Wetlands Assessment	NC Wetlands	Overlay Analysis	Bladen Co, NC; Brunswick Co, NC; Columbus Co, NC; Robeson Co, NC; Dillon Co, SC; Florence Co, SC; Horry Co, SC; Marion Co, SC	UA:22%	Low	The quality and limitation associated with the input data will directly affect the accuracy of the results.
North Carolina Overlay Analysis	NC DEQ	Overlay Analysis	North Carolina	UA: 27-63% PA: 38-88%	Low	The quality and limitation associated with the input data will directly affect the accuracy of the results; omission errors found with smaller wetlands and commission errors with larger wetlands (>1 acre).
SCDOT Wetland Likelihood	SCDOT	Overlay Analysis	South Carolina	UA: 83% PA: 27%	Low	The quality and limitation associated with the input data will directly affect the accuracy of the results; commission and omission errors are probably with larger and smaller wetlands.

[3] https://pro.arcgis.com/en/pro-app/latest/help/analysis/image-analyst/accuracy-assessment.htm

Method	Source	Method Type	Location	Accuracy*	Level of Effort	Limitations
ArcHydro Wetland Identification Model	ESRI	Machine Learning	Not Applicable	PA: 80-90% UA: 22-69%	Medium	Requires iterative process to identify optimal parameters and build the best performing model; requires multiple model runs due to processing extent limitations.
Wetland Intrinsic Potential Tool	University of Washington TerrainWorks	Machine Learning	Hoh River Watershed, WA	UA:91.97%	Medium-High	Will require more coding experience than the ArcHydro Wetland Identification Model and has similar limitations.
Sky Wave	CDM Smith	Machine Learning	Not Applicable	Not Provided	High	Would require hiring a contractor to acquire the multispectral drone imagery and conduct the wetland mapping analysis.
Maximum Entropy Modeling	NC DEQ	Machine Learning	Northern Outer Piedmont (NOP) Level IV in NC	UA:17-18% PA: 75%	Medium – High	Will require an iterative process to identify optimal parameters and build the best performing model. Results may be comparable to a more simplified overlay analysis.
AI Deep Learning Model for Mapping Wetlands	CIC, EPRI	Deep Learning	Kent Co, DE; Mille Lac Co, MN; St. Lawrence Co, NY	UA: 94%	High	Complex model that will require large amounts of data storage and computational capacity (cloud computing).
Wetland Screening Tool	Skytec	Deep Learning	Tennessee	UA: 70-85%	High	Would require hiring a contractor as the model is not publicly available.

**UA = User's Accuracy, PA = Producer's Accuracy*

Overlay Analysis Examples

Wetlands-At-Risk Protection Tool (WARPT)

Source: Center for Watershed Protection (CWP)
Method Type: Overlay Analysis
Data Needs: Required data includes hydric soils, high-resolution DEM, and NWI. Optional data includes vegetation, floodplains, and orthoimagery.
Accuracy: 23% (UA)
Level of Effort: Low
Resource Link(s):

- Manual: https://owl.cwp.org/257lcbl/

Description:
The Wetlands-At-Risk Protection Tool, or WARPT, is a process for local governments and watershed groups that acknowledges the role of wetlands as an important part of their community infrastructure and is used to develop a plan for protecting at-risk wetlands and their functions. Wetlands-at-risk are those that are vulnerable to impacts from development or other land use activities and that have little protection from these impacts through federal, state, or local measures. The WARPT includes an overlay analysis that identifies potential wetlands through the use of wetland indicator data layers. Hydric soils are probably the best and most readily available wetland indicator layer to use for this analysis. However, hydric soils can overestimate the extent of wetlands (Tiner, 1999). In addition, the absence of hydric soil should not be construed to mean that the area is always non-wetland, since some wetlands exist on hydric substrates or develop under prolonged saturated conditions where typical hydric soils do not form. It is therefore recommended that hydric soils be used in conjunction with other available wetland indicator layers, such as floodplains and topographic depressions, to identify areas that have high potential for wetland presence. Simultaneous viewing of these wetland indicator layers allows you to determine where overlap occurs, and subsequently where wetlands are most likely to exist. If the results are to be incorporated into local wetland maps and assigned wetland functions, field verification of all 'potential wetlands' is needed to confirm that they exist. A case study in Frederick County, MD found that approximately 23% of wetlands were correctly identified through a weighted overlay analysis. The use of headwater streams as an indicator layer is believed to have led to an overestimate of wetland presence. Additional field verification would be required to test this hypothesis.

Southeast Isolated Wetlands Assessment (SEIWA)

Source: NC Wetlands
Method Type: Overlay Analysis
Data Needs: LiDAR DEM, NWI, infrared imagery, soils (Hydric, Ponded, Floodplain), USGS National Hydrography Dataset, Floodplains, Land cover, roads, Habitat (NC and SC Natural Heritage Program data)
Accuracy: 22% (UA)
Level of Effort: Low.
Resource Link(s):

- Website: https://www.ncwetlands.org/project/mapping-assessing-isolated-wetlands/
- Report: https://www.ncwetlands.org/wp-content/uploads/Assessing-Isolated-Wetlands-in-N-and-S-Carolina-2010-Final-Report.pdf

Description:
The Southeast Isolated Wetland Assessment (SEIWA) explored the condition and history of geographically isolated wetlands in an 8-county portion of the coastal plain of North and South Carolina. SEIWA employed a phased approach based on three levels of wetland assessment described by EPA (U.S. EPA, 2006): Level 1, which used geographical information systems (GIS) to identify isolated wetlands in the study area; Level 2, which was a rapid on-the-ground assessment of the type and condition of a random sample of Level 1 sites; and Level 3, detailed field assessments to measure the hydrologic conditions, water quality, and biota (amphibians, macroinvertebrates, and plants) of selected isolated wetland sites.

The Level 1 GIS approach consisted of an overlay analysis of physical, hydrologic, and biological characteristics relevant to geographically isolated wetlands. DEMs and a GIS "sink" algorithm were used to create candidate polygon sinks representing low spots in the landscape that could be isolated wetlands. The polygons were then overlaid with hydrography, soils, floodplains, wetland, and land cover layers on infrared imagery to remove obviously connected features and score the remaining features as to their likelihood to be isolated wetlands. Overall, approximately 22% of predicted isolated wetlands were found to be accurately determined. These results show that while the method can identify wetlands that might be isolated, the high-resolution

LiDAR data had trouble identifying the small ditches and other drainage structures that can connect an isolated wetland with downstream navigable waters, causing the high false positive rate.

North Carolina Overlay Analysis

Source: North Carolina Department of Environmental Quality, Division of Water Resources
Method Type: Overlay Analysis
Data Needs: Hydric soils, topographic depressions, NWI
Accuracy: 27-63% (UA); 38-88% (PA)
Level of Effort: Low
Resource Links:
https://www.ncwetlands.org/wp-content/uploads/NCDWR-WetlandModelingReport-2021.pdf
Description:
An unweighted overlay analysis was used to identify potential wetlands in North Carolina. Hydric soils were obtained from the Natural Resources Conservation Service soils geodatabase and hydrologic sinks identified from a 20-ft resolution DEM were used as a surrogate for topographic depressions. A modified NWI was also used where features not commonly considered wetlands, such as deepwater, open water, and lotic systems were removed. Seven models were prepared using a combination of the hydric soils, hydrologic sinks, and NWI. While many wetlands were correctly identified by the combined models, the models also tended to overestimate the presence of wetlands, resulting in relatively large frequency of false positives. The Mid-Atlantic Coastal Plain ecoregion had the best balance of over- and under-prediction, while over-prediction for most models was much worse in the Blue Ridge and Piedmont ecoregions. Most models had errors of omission for smaller wetlands and errors of commission for larger wetlands (>1 ac). The overlay analyses using hydric soils and the NWI had similar results as Maximum Entropy Modeling (Maxent) that is further described under the Machine Learning Examples.

SC DOT Wetland Likelihood

Source: SCDOT
Method Type: Overlay Analysis
Data Needs: Hydric soils/SSURGO, topographic depressions, NWI, LULC
Accuracy: 83% (UA)
Level of Effort: Low
Resource Links: https://rosap.ntl.bts.gov/view/dot/32668/dot_32668_DS1.pdf
Description:
For this project they combined the prediction value of NWI, SSURGO soils, and SCDNR land use/cover (LULC) wetlands data to produce a single layer that represents high confidence in the mapped wetlands. Additionally, there was a desire to produce a model that resulted in the extremes – the minimum and maximum wetland impacts expected from road/bridge improvement projects.

The quality of the wetlands likelihood layer and the NHD-based streams data will vary across the state. There are several explanations. First, the source imagery used for creating both the NWI and topographic maps to support the streams data are from different years, with an elapsed time of some 30 years across the state. Changes to wetlands (both destructive and regrowth areas) will have occurred and are not reflected in the final wetlands likelihood layer. The NHD streams data were created from the consistent set of 1:24,000 scale topographic maps; however, the consistency in the analyst identification of streams was not evident. And the NHD data largely omit the headwater streams. Secondly, the geography of the state varies from the coastal plain through the piedmont to the upstate. Many of the counties in South Carolina are creating their own versions of ditches/streams with different criteria for defining these features. While it is possible to merge the diverse county derived data the composition will create a very heterogenous patchwork for the quality of stream locational data in the state. Similarly, the incorporation of parcel-level land use codes is highly variable in the state and problematic to incorporate. Thus, the use of the wetlands likelihood layer and NHD streams should be conducted in the context of geographic variation in quality.

Machine Learning Examples

Arc Hydro Wetland Identification Model (WIM)

Source: ESRI
Method Type: Machine Learning – Random Forest Model
Data Needs: Required data includes a high-resolution LiDAR DEM and verified wetland/non-wetland coverage (i.e., ground-truth data). A surface water raster is also recommended.
Accuracy: 80-90% (PA); 22-69% (UA)
Level of Effort: Medium. An iterative process will be required to identify optimal model parameters for the study area and multiple model runs due to the maximum size of the processing extent, but the model framework already exists and there is guidance, documentation, and blogs for assistance as difficulties arise.
Resource Link(s):

- WIM Framework & Workflow Document: https://downloads.esri.com/ARCHYDRO/ArcHydro/Doc/Arc%20Hydro%20-%20Wetland%20Identification%20Model.pdf
- Blog: https://community.esri.com/t5/water-resources-blog/the-wetland-identification-model-wim-a-new-arc/ba-p/884298
- Webinar: https://mediaspace.esri.com/media/t/1_f4st9x7v

Description:
The Wetland Identification Model (WIM) is an automated geoprocessing workflow created through research at the University of Virginia. The workflow uses LiDAR DEMs to derive topographic metrics that describe hydrologic drivers of wetland formation and uses these as predictors of wetland areas through the random forests algorithm (Breiman, 2001). The WIM consists of three main parts: preprocessing, predictor variable calculation, and classification and accuracy assessment. Final model outputs are wetland predictions and an accuracy report. WIM is implemented as a series of Arc Hydro Python Script Tools for ArcGIS Pro (version 2.5 and higher).

It was originally developed and evaluated for environmental planning applications in Virginia, specifically to streamline the wetland permitting process by providing accurate wetland inventories that limit manual surveying to likely wetland areas. Success in regions beyond those the model was originally developed for in VA will depend on the quality of the DEM and available ground truth data. Optimal WIM parameters will vary by the landscape and application and it will be an iterative process to build the best-performing model for a specific study area and end goal. Due to raster size limitations, the predictor variable extent should not be larger than a HUC-12 watershed with 1-meter resolution, and smaller watersheds are encouraged if available. The Town of Bluffton is primarily within the extent of three HUC 12 watersheds and therefore may require multiple model runs.

Wetland Intrinsic Potential Tool

Source: University of Washington; TerrainWorks
Method Type: Machine Learning – Random Forest Model
Data Needs: four-band aerial imagery – 1m, LiDAR DEM, Digital Surface Model (DSM), SSURGO data – depth to any restricted layer & hydraulic conductivity
Accuracy: 91.97% (UA)

Level of Effort: Medium to High. This tool is currently available as an ESRI ArcGIS toolbox and there may be the ability to integrate this analysis as part of the WIM. The WIP does use a combination of R and Python scripts, so experience with code is needed. Similar to the WIM, optimal model parameters would need to be explored for the study area.

Resource Link(s):

- 2023 Webinar Recording: https://nawm.org/nawm/nawm-category/2023-past-wetland-mapping-consortium-webinars#wmc0208
- 2023 Webinar slide (PDF): https://nawm.aswm.org/pdf_lib/mapping_webinar/the_wetland_intrinsic_potential_tool_020823_halabisky.pdf
- Paper: https://hess.copernicus.org/articles/27/3687/2023/hess-27-3687-2023.pdf
- https://www.ncwetlands.org/wp-content/uploads/NCDWR-WetlandModelingReport-2021.pdf

Description:

The Wetland Intrinsic Potential (WIP) tool is based on a wetland indicator framework commonly used on the ground to detect wetlands through the presence of three wetland indicators: hydrophytic vegetation, hydrology, and hydric soils. It was designed to improve the detection of wetlands with a specific focus on increasing detection of cryptic wetlands obstructed by vegetation canopy, influenced by shadows from nearby objects and steep topography, and wetlands that do not have visible standing water for some part of the year. The WIP uses a random forest model with spatially explicit input variables that represent all three wetland indicators, including novel multi-scale topographic indicators that represent the processes that drive wetland formation, to derive a map of wetland probability. The WIP tool can identify areas conducive to wetland formation while providing a flexible approach that can be adapted to diverse landscapes. The WIP tool is implemented as an ArcGIS toolbox using a combination of R and Python scripts. Components of the WIP are currently being integrated into ESRI's Wetland Identification Model (WIM), specifically multi-scale terrain indices and inclusion of point-based training data.

The WIP tool was developed and tested in the Pacific Northwest coastal area of Washington State, but has also been applied to several new and distinct geographies, including the Skagit Basin of Washington and the Island of Hawaii. For application of the WIP tool in a new area, the wetland-indicator framework would need to be revisited considering the types of wetlands in the study area and if new remote sensing proxies should be added.

Sky Wave (Remote Sensing and Machine Learning)

Source: CDM Smith

Method Type: Machine Learning

Data Needs: Multispectral drone imagery

Accuracy: Not provided

Level of Effort: High. This method would involve hiring a contractor to complete the wetland mapping work. High costs are expected.

Resource Link(s):

- Website: https://www.cdmsmith.com/en/news/cdm-smith-launches-sky-wave-drones-machine-learning-and-remote-sensing-for-environmental-projects
- Fact Sheet: Sky_Wave_at_CDM_Smith_2023.pdf

Description:

Sky Wave is an advanced fixed wing drone and mobile command center used for data collection and assessments. It combines drones, remote sensing, and machine learning to solve complex environmental problems. A patent-pending drone data collection method that reduces field work, increases accuracy, and facilitates drone data integration into AI models. This data collection method would provide the most recent data collected by the drones for wetland mapping. However, specific examples and methods for wetland mapping were not provided.

Maximum Entropy Modeling (Maxent) in Great Smoky Mountains National Park

Source: North Carolina Department of Environmental Quality, Division of Water Resources
Method Type: Machine Learning
Data Needs: Field-identified wetlands to use as training data; elevation above sea level and eight other variables derived from a DEM; climatic data including average annual rainfall, and minimum and maximum annual temperature; vegetation community type from the USGS GAP Analysis Program; and soils data, including drainage class, available water supply at a variety of depths, and hydric status.
Accuracy: 17-18% (UA); 75% (PA)
Level of Effort: Medium to High
Resource Links:
https://biodiversityinformatics.amnh.org/open_source/maxent/
https://www.ncwetlands.org/wp-content/uploads/NCDWR-WetlandModelingReport-2021.pdf
Description:
Maximum entropy (Maxent) is a machine learning method that has been widely adopted by ecologists in recent years. Its advantage is that it only requires presence data for training the model, whereas almost all other modeling approaches also require absence data. Wetland suitability models incorporating 18 environmental variables were developed for the portion of the Great Smoky Mountains National Park in North Carolina. Only five of the variables were major contributors to the final model: hydric soils, vegetative community, slope, elevation, and minimum temperature. A potential issue identified with including too many variables is that it can lead to modeling "noise" (such as the variability inherent in the data) rather than meaningful environmental conditions. A large number of variables were found to be strongly correlated with one another, such as the soils and topographic variables. The MaxEnt models were compared to overlay models for all data and were found to have similar results as overlay analyses using hydric soils and the NWI.

Deep Learning Examples

Artificial Intelligence Deep Learning Model for Mapping Wetlands

Source: Chesapeake Conservancy Chesapeake Innovation Center (CIC); Electric Power Research Institute (EPRI)
Method Type: Deep Learning – Convolutional Neural Network
Data Needs: NWI reference data (vector -> binary raster), Multispectral data (NAIP and Sentinel-2 satellite), LiDAR (intensity -point cloud data in LAS format and geomorphons - bare earth DEMs (1m))
Accuracy: 94% (UA)
Level of Effort: High. **–** The model will require retraining for the new area of interest to maximize wetland identification precision. It also will require large data storage due to the use of high-resolution datasets and is computationally intensive requiring cloud computing. See process under Section 2.4 of the peer-reviewed study. Video: Tool demo
Resource Links:

- Website: https://www.chesapeakeconservancy.org/2023/01/10/artificial-intelligence-deep-learning-model-for-mapping-wetlands-yields-94-accuracy/
- Paper: https://www.sciencedirect.com/science/article/pii/S0048969722077257?via%3Dihub
- Storymap: https://storymaps.arcgis.com/stories/4f98297b48a94efbbbe0199681539980

Description:
Chesapeake Conservancy trained a machine learning (convolutional neural network) model for high-resolution (1m) wetland mapping with publicly available data from three areas: Mille Lacs County, Minnesota; Kent

County, Delaware; and St. Lawrence County, New York. The site in Kent County is located on the outer Atlantic coastal plain where a large portion of the wetlands are marine and estuarine. Multispectral data utilized include NAIP and Sentinel-2 that have a balance of spatial and temporal resolution. The model also utilizes two datasets derived from airborne LiDAR: intensity and geomorphons. Wetlands and other inundated areas often exhibit far lower intensity values than areas that are not inundated because inundated soils absorb LiDAR pulses rather than reflect them. A geomorphon pattern of highly repeating series of small, irregular ridges, valleys, pits, flats, and footslopes along an otherwise flat or non-sloping area on the landscape was also found to correspond to wetland areas caused by dense, low-growing, herbaceous vegetation common in many wetlands in combination with the low gradient of wetland areas.

The full model, which requires local training data provided by state wetlands data and the National Wetlands Inventory (NWI), mapped wetlands with 94% accuracy. Generating data for model training involved the sampling of 256 x 256 pixels x 28 band chips from images at a set of random locations inside, outside, and along the edge of confirmed wetlands within each study area. For areas along wetland boundaries, 5,000 candidate locations were generated and only those at least 256 meters from their nearest neighbor were kept as a part of the training dataset for the model. Additionally, the training dataset included randomly sampled locations inside and outside of confirmed wetlands with an initial 25,000 candidate locations for each scenario. Locations outside of wetlands were then pared down to only those locations that were 256m from their nearest neighbor. Whereas, for areas inside of wetland areas, sample locations were kept only if a surrounding 256 x 256-pixel window had at least 50% wetland pixels. This resulted in a total of 20,367 locations across all study sites that were split into the neural network's training (70%) and testing (30%) datasets.

The deep learning model generates a probability map that predicts the likelihood of wetland presence across the landscape. All training was performed on the Microsoft Azure Machine Learning Studio platform using NVIDIA Tesla K80 machines with 2 GPU cores.

Wetland Screening Tool

Source: Skytec, LLC
Method Type: Deep Learning
Data Needs: LiDAR, high-resolution aerial or satellite imagery, NAIP imagery, existing wetland boundaries from regulatory reports, Natural Heritage data on rate, threatened, or endangered elements/habitats, NWI data
Accuracy: 70 – 85% (UA)
Level of Effort: High. This approach would involve hiring a third-party to develop and test the predictive wetland model for the Town of Bluffton, SC.
Resource Link(s):

- Blog Webpage
- TN Wetland Screening Tool: Project Fact Sheet
- TN Wetland Screening Tool: Storymap

Description:
Skytec LLC, in partnership with the Tennessee Department of Environment and Conservation, developed a predictive wetland model with a 3-meter resolution for the State of Tennessee that utilized an enhanced version of the ESRI Wetland Identification Model, optimized for large-scale application across statewide geography. The model integrates Deep Learning tools to identify wetland features in aerial or satellite imagery. Key inputs for the model included LiDAR-derived predictor variables (topographic wetness index, curvature, cartographic depth to water), high-resolution imagery, and approximately 75,500 acres of wetland training data. The raw data was post-processed to remove roadways, National Hydrography Dataset waterbodies, and built areas from land cover data because the model tends to overpredict the occurrence of wetlands within

highly developed areas where culverts and stormwater systems affect flow accumulation models and other LiDAR derived predictor variables. This modified Wetland Identification Model does not appear to be publicly available, and specifics about the model development are not provided. This approach would likely involve hiring Skytec for their services.

Data Availability

To help inform the recommendation of an approach to update wetland mapping for the Town of Bluffton, CWP led a review of available data to support the mapping methods described in this report. This review included both "mapped wetland data" and "wetland indicator layers." The review of mapped wetland data identified what wetland data besides the NWI are available for Bluffton and assessed their accuracy and applicability for updating Town wetland maps. Wetland indicator layers are used to infer where wetlands might be located and are supplemental to mapped wetland layers. Wetland indicator layers can be used to update and verify mapped wetlands using overlay analysis, machine learning, or deep learning methods.

Mapped Wetland Data

Table 2 provides a brief overview of the existing mapped wetland data available for use by the Town of Bluffton and is followed by a detailed description of each dataset. While some wetland datasets are available, their limitations, particularly regarding spatial resolution and minimum mapping unit, render them generally unsuitable for the Town's precise local wetland mapping goals. Many of these datasets are designed for regional assessments and lack the detail required for local applications. The NWI is the most comprehensive and accurate representation of wetlands currently available for the Town. However, the NWI is outdated as it is based on imagery from 2006 and 2011 and is limited by not including wetlands smaller than 0.5 acres. The 30-meter resolution datasets – GAP/LANDFIRE, C-CAP National Wetland Potential, C-CAP Regional Land Cover, and NLCD – are largely unsuitable for the precise, local-scale wetland mapping required by the Town due to the resolution. The recently released 1-meter resolution C-CAP Regional Land Cover dataset for coastal areas provides more appropriate and useful data for local wetland identification applications. However, only waterbodies are currently available at the 1-meter resolution.

Table 2. Available mapped wetland data

Data	Source	Geographic Area	Accuracy	Date Published/ Update Frequency	Applicability to Town Goals
National Wetlands Inventory	USFWS	United States	Medium	2024 (based on 2006 and 2011 imagery)	Base wetland data that would need to be further refined to increase accuracy and include all wetlands regardless of size or type
GAP/LANDFIRE National Terrestrial Ecosystems	USGS	United States	Not Provided	2011	Not applicable – data is provided at 30-meter resolution and intended for regional scale assessment
C-CAP National Wetland Potential	NOAA	U.S. contiguous coastal areas	Not provided	Published 2020 Updated 2024	While results are not directly applicable due to the 30-meter resolution, the method may be applicable for an overlay analysis using finer-scale resolution data inputs,
C-CAP Regional Land Cover - Coastal	NOAA	U.S. contiguous coastal areas	Not Provided	Published 2016 Updated 2023 5-year update cycle	30-m and 1-m land cover data for U.S. coastal areas.

Data	Source	Geographic Area	Accuracy	Date Published/ Update Frequency	Applicability to Town Goals
					Potentially useful to refine existing wetland data.
National Land Cover Database (NLCD)	USGS; MRLC	United States	54-94% (UA); 27-88% (PA)	2016; Annual updates	Not applicable – data is provided at 30-meter resolution and intended for regional scale assessment

National Wetland Inventory

Source: U.S. Fish and Wildlife Service (USFWS)
Geographic Area: United States
Data Type: Vector
Accuracy: 98% (PA)
Resolution/Scale: 1:12,000
Date Published: May 1, 2024
Links:

- https://www.fws.gov/program/national-wetlands-inventory/wetlands-data
- Bluffton, SC feature Layer (2023)

Description:
The purpose of mapping wetlands and deepwater habitats through NWI is to produce medium resolution information on the location, type and size of wetland resources that are accurate at the 1:12,000 scale (USFWS, 2020). The NWI wetlands are identified from high altitude imagery, and are identified based on vegetation, visible hydrology, and geography. The accuracy of the identified wetlands depends on the quality of the high latitude imagery, the analyst's experience, amount and quality of additional data, and the amount of the ground truth verification work. The NWI wetlands data is developed using the biological definition of wetlands, which may be different from wetland boundaries based on federal definitions of wetlands under the CWA. The data was not designed to stand alone and were originally developed as topical overlays to the U.S. Geologic Survey 1:24,000 or 1:25,000 scale topographic quadrangles or digital imagery. The USFWS did not design or intend for these procedures to yield legal or regulatory products.

NWI data relevant to the Town of Bluffton was last updated with imagery from 2006 and 2011[4]. This data typically does not include wetlands smaller than one to three acres (FGDC, 2009), and from the recorded NWI Data Limitations:

> Certain wetland habitats are excluded from the National mapping program because of the limitations of aerial imagery as the primary data source used to detect wetlands. These habitats include seagrasses or submerged aquatic vegetation that are found in the intertidal and subtidal zones of estuaries and nearshore coastal waters. Some deepwater reef communities (coral or tuberficid worm reefs) have also been excluded from the inventory. These habitats, because of their depth, go undetected by aerial imagery. By policy, the Service also excludes certain types of "farmed wetlands" as may be defined by the Food Security Act or that do not coincide with the Cowardin et al. definition.

GAP/LANDFIRE National Terrestrial Ecosystems

Source: U.S. Geological Survey (USGS)
Geographic Area: United States
Data Type: Raster (30-meter)

[4] https://fwsprimary.wim.usgs.gov/wetlands/apps/wetlands-mapper/

Accuracy: Not Provided
Date Published/Updated and Update Frequency: 2011
Link: https://www.usgs.gov/programs/gap-analysis-project/science/land-cover-data-overview
Description:
The GAP/LANDFIRE National Terrestrial Ecosystems dataset version 3.0 is a 2011 update of the National Gap Analysis Program Land Cover Data - Version 2.2 for the conterminous U.S. that includes detailed vegetation and land cover patterns. The dataset incorporates the Ecological System classification system developed by NatureServe to represent natural and semi-natural vegetation, where ecological systems are defined as "groups of plant community types that tend to co-occur within landscapes with similar ecological processes, substrates and/or environmental gradients." Ecological systems provide detailed information on the vegetative communities of an area that is not available in most other regional or national land cover products. This level of thematic detail makes possible the construction of wildlife habitat distribution models, and the construction of complicated hydrology and fire dynamics models, and many other applications. The dataset uses a 30-meter pixel cell and in most areas a minimum mapping unit of 0.4 ha (1 acre) this means that small patches of vegetation can be missed in the modeling process. By nature of their patchy distributions and frequently small extents wetlands, riparian habitats and rare habitat types can be the most frequently missed types. The dataset was created for regional terrestrial biodiversity assessment and is not intended to be used at scales larger than 1:100,000. This dataset identifies several subcategories within the Forest & Woodland and Shrub & Herb vegetation categories that represent specific wetland ecosystem types, such as Atlantic Coastal Plain Central Fresh-Oligohaline Tidal Marsh, Atlantic Coastal Plain Peatland Pocosin, and Atlantic Coastal Plain Clay-Based Carolina Bay Forested Wetland.

C-CAP National Wetland Potential
Source: National Oceanic and Atmospheric Agency (NOAA)
Geographic Area: U.S. Contiguous coastal areas
Data Type: Raster (30-meter)
Accuracy: Not Provided
Date Published/Updated: Published October 30, 2020/ Updated May 8, 2024
Link(s):
- https://coast.noaa.gov/digitalcoast/data/ccapwetland.html
- https://www.fisheries.noaa.gov/inport/item/48357

Description:
Data created to inform likelihood of wetland and assess areas for potential mitigation or restoration. The probability rating which covers landcover mapping provides a continuum of wetness from dry to water. The layer is not a wetland classification but provides the wetland likelihood at a specific location. The rating was developed through a modelling process combining multiple GIS and remote sensing data sets including soil characteristics, elevation, existing wetland inventories, hydrographical extents and satellite imagery.

This product uses a combination of wetland-related data and modeling methods to determine how likely an area is to be a wetland. This combination provides a robust representation of potential wetland features and a superior means of accounting for areas with missing coverage or varying vintages. Input data include the National Wetland Inventory (NWI), Soil Survey Geographic (SSURGO) database, National Hydrography Dataset (NHD), National Elevation Dataset (NED), and Landsat Satellite Imagery.

The ratings these data provide may be useful in assessing areas as past or current wetlands or for evaluating sites for wetland mitigation or restoration. These data were produced as part of NOAA's coastal land cover efforts and were used to improve wetland categories within C-CAP regional land cover maps for the continental U.S.

C-CAP Regional Land Cover Data - Coastal

Source: National Oceanic and Atmospheric Agency (NOAA)
Geographic Area: U.S. Contiguous coastal areas
Data Type: Raster (30-meter)
Accuracy: Not Provided
Date Published/Updated and Update Frequency: Published October 17, 2016 / Updated September 5, 2023; 5-year update frequency
Links:

- https://coast.noaa.gov/digitalcoast/data/ccaphighres.html
- https://www.fisheries.noaa.gov/inport/item/48336

Description:
The NOAA Coastal Change Analysis Program (C-CAP) produces national standardized land cover and change products for the coastal regions of the U.S. C-CAP products inventory coastal intertidal areas, wetlands, and adjacent uplands with the goal of monitoring changes in these habitats, on a one-to-five-year repeat cycle. Currently only regional land cover data is available for SC. It is produced at a 30-meter resolution for the coastal areas of the contiguous U.S. Data and is updated from multiple dates of remotely sensed Landsat imagery and ancillary information. Most areas have 20 years of data, with some areas having up to 40 years. 1-meter resolution land cover water data (Link) for SC was published September 30, 2023. The 1-m resolution data is referred to as "CCAP High Resolution Version 2".

NOAA's data use restrictions state that the C-CAP data is not to be used for machine learning algorithm applications "for a period of 5 years from its date of creation" related to contract agreements with the data producer. Additionally, the existing high- resolution land cover data is split between legacy pre-2024 and post-2023 data which are not designed to be compared based on the different methodologies and technologies used.

National Land Cover Database (NLCD)

Source: USGS; Multi-Resolution Land Characteristics (MLRC) consortium
Geographic Area: Lower 48 United States, Hawaii, Alaska and Puerto Rico
Data Type: Raster (30-meter)
Accuracy: 54-94% (UA) and 27-88% (PA) for all land cover years depending on the CONUS reference data year.
Date Published/Updated and Update Frequency: Most recent product published Oct 16, 2024/ Updated Annually
Link:

- Main Website: https://www.mrlc.gov/data
- NLCD User Guide
- Reference Data Product: https://www.sciencebase.gov/catalog/item/6813a71bd4be023163051775
- Validation Tables: https://www.usgs.gov/data/annual-national-land-cover-database-nlcd-collection-10-validation-tables

Description:
The NLCD is a comprehensive land cover product mapping the lower 48 United States, Hawaii, Alaska and Puerto Rico from decadal Landsat satellite imagery and other supplementary datasets. The purpose of the NLCD is to provide the Nation with nationally complete, current, consistent and public domain information on the Nation's land cover. Land cover information is critical for local, state and federal managers and officials to assist them with issues such as assessing ecosystem status and health, modeling nutrient and pesticide runoff, understanding spatial patterns of biodiversity, land use planning, deriving landscape pattern metrics and

developing land management policies. The annual NLCD provides a suite of 6 geospatial raster products that includes a categorical sixteen-class land cover classification system which includes Woody Wetlands and Emergent Herbaceous Wetlands.

Town of Bluffton Wetland Delineations from Permitted Projects

The Town of Bluffton provided PDF plan sets for multiple permitted projects that included wetland delineations. The plans were reviewed for the ability to georeference them using either coordinates on the plans or identifiable features that align with available GIS data, including parcel boundaries and road intersections. A total of four plan sets that could be georeferenced were identified, including New Riverside, Bluffton Park, Buckwalter BMH and Harris Teeter within the Buckwalter Commons development. In addition, the Town provided a polyline layer for wetlands within the Palmetto Bluff Phase 2 development and associated PDF plans.

Wetland Indicator Data

In addition to the NWI and other mapped layers, the following types of datasets are commonly used in wetland identification to identify the locations of characteristics that could support wetland ecosystems:

1. Topography: Topographic datasets, such as DEMs, LiDAR, and contours, can be used to identify topographical depressions, where wetlands are more likely to be found. Metrics such as slope and flow accumulation can also be derived from topographic datasets to be used in indices such as the Topographic Wetness Index that predicts relative surface wetness and provides an indication of where wetlands may be more likely to occur.
2. Soils: Soil datasets identify hydric soils which are permanently or seasonally saturated by water, resulting in anaerobic conditions, as found in wetlands. Hydric soils are poorly or very poorly drained and under natural conditions, these soils are either saturated or inundated long enough during the growing season to support the growth and reproduction of wetland vegetation. Hydric soils are part of the legal definition for wetlands in the United States and are used to identify wetland areas that require a permit issued by the Army Corps of Engineers under Section 404 of the Clean Water Act prior to any ground disturbing activities. The depth to water table may also be included in soils datasets and can be used to indicate groundwater outcrop locations where wetlands may be more likely to occur.
3. Hydrology: Hydrologic layers such as surface water features and floodplains may be used to identify locations where certain types of wetlands such as riverine or lacustrine are more likely to be present. Floodplains can be indicators of wetlands due to their low-lying topography, where water naturally accumulates, and their close proximity to water bodies like rivers and streams. Areas within a floodplain often experience frequent soil saturation and can support water-loving vegetation, which are defining characteristics of wetlands.
4. Aerial or Satellite Imagery: Multi- and hyper-spectral satellite and aerial imagery data are key for manually interpreting and digitizing wetlands using heads-up methods digitization and provide the basis for identifying key spectral or non-spectral signatures that indicate wetland characteristics using machine learning methods. Aerial imagery can also be used with any method to provide supporting detail about plant vegetation type and soil moisture using the specified bands available.

A summary of available datasets for the Town of Bluffton is provided in Table 3 and the following section.

Table 3. Available wetland indicator data

Data Type	Data	Source	Geographic Area	Date Published/ Update Frequency	Applicability to Town Goals
Topography	LiDAR	USGS	21,423 square miles across South Carolina	2020	Use to identify depressional areas where wetlands may be present for overlay analysis
	LiDAR	SC DNR	Beaufort County, SC	2013	
Soils	Soil Survey Geographic Database	NRCS	Contiguous US	2025	Use to identify hydric soils and depth to water table for overlay analysis
Hydrology	National Flood Hazard Layer	FEMA	US	2021	Use to indicate potential locations of riparian wetlands as part of overlay analysis
	3D Hydrography Program	USGS	US	2025	Use to identify surface water features near which certain types of wetlands may potentially be located for overlay analysis
Aerial or Satellite Imagery	Aerial imagery	Town of Bluffton	Town of Bluffton	2024	Could be used for machine learning approach if training dataset is available
	National Agriculture Imagery Program	USDA	South Carolina	2023	
	Sentinel 2	Copernicus Data Space Ecosystem	Global	2024	

2020 USGS LIDAR: SAVANNAH PEE DEE, SC

Source: USGS
Geographic Area: ~21,423 square miles across South Carolina
Data Type: LiDAR; Elevation
Accuracy:

- Positional Horizontal Accuracy = +/- 35.5 – 45.5 cm at a 95% confidence level (varies by block).
- Vertical Positional Accuracy: 8.7 cm at 95% confidence level - tested to meet vertical root mean square error (RMSEz) in open terrain.

Date Published/Updated and Update Frequency: Published 09/04/2020
Link: https://coast.noaa.gov/dataviewer/#/lidar/search/where:ID=9436/details/9436
Description:
This data was collected as part of the U.S. 3D Elevation Program to support the 3DEP mission, the Natural Resources Conservation Service (NRCS) high resolution elevation enterprise program, and the Federal Emergency Management Agency (FEMA) Risk Mapping, Assessment and Planning (MAP) program, as well as many South Carolina state and local agencies. Processed, classified lidar point cloud data tiles in LAS 1.4

format. The SC Savannah Pee Dee 2019 B19 lidar project called for the planning, acquisition, processing, and production of derivative products of QL 1 and QL2 lidar data to be collected at a nominal pulse spacing (NPS) of 0.35 and 0.71 meters. Project specifications were based on the U.S. Geological Survey National Geospatial Program Base Lidar Specification, Version 1.3. The data was developed based on a horizontal datum/projection of NAD83 (2011) State Plane South Carolina (FIPS 3900) International Feet (EPSG 6570), and a vertical datum of NAVD88 (GEOID18) US Survey Feet. The Town of Bluffton provided a 2-foot DEM that was developed from this LiDAR dataset.

2013 SC DNR Lidar: Beaufort County

Source: South Carolina Department of Natural Resources
Geographic Area: Beaufort County, SC
Data Type: LiDAR; Elevation
Accuracy:

- Vertical Accuracy (cm): 6 - Tested vertical root mean square error (RMSEz)
- Horizontal Accuracy (cm): 100 - Not tested

Date Published/Updated and Update Frequency: Published 08/2013
Link: https://coast.noaa.gov/dataviewer/#/lidar/search/where:ID=5104/details/5104
Description:
Lidar data was acquired to provide high-resolution topographic data for floodplain mapping. LMSI provided high accuracy, calibrated multiple return LiDAR for roughly 785 square miles covering Beaufort County, South Carolina. The nominal point spacing for this project was at least 4 points per square meter. Dewberry used proprietary procedures to classify the LAS according to project specifications: 1-Unclassified, 2-Ground, 7-Noise, 8-Model Key Points, 9-Water, 10-Ignored Ground, 11-Withheld Points, 13-Bridges and Culverts. Dewberry produced 3D breaklines and combined these with the final LiDAR data to produce seamless hydro-enforced DEMs for the 982 tiles (5000 ft x 5000 ft) that cover the project area

Soil Survey Geographic Database (SSURGO)

Source: Natural Resources Conservation Service (NRCS)
Geographic Area: Contiguous U.S.
Data Type: Vector
Accuracy:
Date Published/Updated and Update Frequency: Published 12/2024; Last Update 04/11/2025; Updated annually
Link: https://www.arcgis.com/home/item.html?id=06e5fd61bdb6453fb16534c676e1c9b9
Description:
The SSURGO database contains information about soil as collected by the National Cooperative Soil Survey over the course of a century. The information can be displayed in tables or as maps and is available for most areas in the United States and the Territories, Commonwealths, and Island Nations served by the USDA-NRCS. The information was gathered by walking over the land and observing the soil. Many soil samples were analyzed in laboratories. The maps outline areas called map units. The map units describe soils and other components that have unique properties, interpretations, and productivity. The information was collected at scales ranging from 1:12,000 to 1:63,360, with a minimum mapping unit of 1 acre on 1:12,000 scale maps.

Hydric rating is one attribute in the SSURGO data that indicates whether or not a map unit component is classified as a hydric soil. While a soil may satisfy hydric criteria, it is important to note that this means it is likely to be hydric and is dependent on in-situ field surveys for verification.

Water table depth (annual minimum) is also an attribute in the SSURGO data that indicates the shallowest depth to a wet soil layer (water table) at any time during the year expressed as centimeters from the soil surface, for components whose composition in the map unit is equal to or exceeds 15%.

National Flood Hazard Layer (NFHL)

Source: FEMA
Geographic Area: United States
Data Type: Vector
Accuracy: A horizontal accuracy of +/- 38 feet is used to determine compliance with the vertical tolerances defined for each risk class. The range of differences between the ground elevation (defined from the topographic data used for the Flood Risk Project) and the computed flood elevation is between +/- 1.0 foot at the 95% confidence interval for areas with high population within the floodplain and/or high anticipated growth and Special Flood Hazard Areas (SFHAs) with high flood risk to +/- one-half the contour interval at the 85% confidence interval for areas with low population and densities within the floodplain and small or no anticipated growth and SFHAs with low flood risk.
Date Published/Updated and Update Frequency: Published/Updated 03/23/2021
Link:

- GIS Web Services for FEMA NFHL
- GIS Data Download

Description:
The National Flood Hazard Layer (NFHL) data incorporates all Flood Insurance Rate Map (FIRM) databases published by the Federal Emergency Management Agency (FEMA), and any Letters of Map Revision (LOMRs) that have been issued against those databases since their publication date. It is updated on a monthly basis. The FIRM Database is the digital, geospatial version of the flood hazard information shown on the published paper FIRMs.

The FIRM Database depicts flood risk information and supporting data used to develop the risk data. The primary risk classifications used are the 1-percent-annual-chance flood event, the 0.2-percent-annual-chance flood event, and areas of minimal flood risk. The FIRM Database is derived from Flood Insurance Studies (FISs), previously published FIRMs, flood hazard analyses performed in support of the FISs and FIRMs, and new mapping data, where available. The FISs and FIRMs are published by FEMA.

The NFHL consists of vector files and associated attributes produced in conjunction with the hardcopy FEMA FIRM and form the basis for administration of the National Flood Insurance Program (NFIP). The NFHL is made up of several data themes containing both spatial and attribute information. These data together represent the current flood risk for the subject area as identified by FEMA. The attribute tables include SFHA locations, flood zone designations, BFEs, political entities, cross-section locations, FIRM panel information, and other data related to the NFIP.

3D Hydrography Program (3DHP)

Source: USGS
Geographic Area: United States
Data Type: Vector
Date Published/Updated and Update Frequency: Published 3/20/2025; Last Update 7/18/2025; Updated annually
Link:

- GIS Web Services for 3DHP
- GIS Data Download

Description:
As of October 1, 2023, the National Hydrography Dataset was retired and replaced with the 3D Hydrography Program (3DHP) The 3DHP improves the level of detail, currency, and content of hydrography data by deriving (1) three-dimensional (3D) stream network datasets and watersheds from high-quality 3D Elevation Program (3DEP) data and (2) other elevation derivatives to support applications like hydrologic and hydraulic modeling. The 3DHP improves the ability to track information related to water as it moves through the hydrologic cycle by connecting surface-water features traditionally represented in NHD to data about wetlands, engineered hydrologic systems, and groundwater. It also improves the attribution of important hydrologic characteristics like streamflow permanence.

Aerial Imagery
Source: Town of Bluffton GIS
Geographic Area: Bluffton, SC
Data Type: Aerial imagery
Link/Description:
- Blufftonaerial2022: Created and last updated 03/06/2023
- DroneAerials2022 (Orthomosaics): Limited to OldTown, OscarFraiz, and Buckwalter areas within Bluffton, SC. Created and last updated 06/28/2022
- Aerial Timeline Slider: Created 09/09/2021; Updated 08/26/2024. Limited to specific areas in Bluffton, SC. Aerial Photography spanning over 80 years in the Town of Bluffton. Aerial Imagery comes from a variety of sources, most of the early years from USDA, USGS, and other US Government sources, the later years come from a Beaufort County/Town of Bluffton collaboration.
- Current Aerial: Created 05/20/2021; Updated 03/06/2023; Aerial imagery for Bluffton, SC.
- 2020Aerial: Created 03/25/2021; Updated 05/11/2021; Covers Beaufort County.
- Aerial2024: Created and last updated 08/08/2024; Imagery covers the Town of Bluffton, SC.

National Agriculture Imagery Program (NAIP)/USDA_CONUS_PRIME
Source: USDA Farm Production and Conservation Business Center
Geographic Area: South Carolina
Data Type: Raster (60-centimeter)
Accuracy: one meter ground sample distance (GSD) ortho imagery rectified within +/- 6 meters to true ground at a 95% confidence level
Date Published/Updated and Update Frequency:2023 imagery
Link: https://gis.apfo.usda.gov/arcgis/rest/services/NAIP/USDA_CONUS_PRIME/ImageServer
Description: The NAIP imagery program acquires aerial imagery during the agricultural growing seasons (leaf on) in the United States. A primary goal of the NAIP program is to make digital ortho photography available to governmental agencies and the public within a year of acquisition to verify agricultural conditions for USDA programs.

Some of the limitations of NAIP aerial photography are: 1. Many of these sources are not geo-referenced and therefore cannot be added to a base map. 2. Low crop producing counties may have fewer available years of imagery. 3. Early year crop compliance slides have no mapping index and consequently are hard to organize and use. 4. Based on the actual flight date and the type of film, the imagery may be limiting relative to some interpretations. For example, flights in the growing season (e.g. leaf on) may result in misinterpretations of potential wetland features. In natural color images water, wetland understory plants, and drainage patterns may be obscured by the canopy of a mature forested cover. 5. Normal climatic conditions (i.e. pre-flight rainfall patterns) assessed for the flight may still not accurately reflect the actual onsite condition due to local variability. 6. Early year crop compliance slides may experience some fading of colors, although this rarely results in the masking of gross landscape features.

SENTINEL-2

Source: Copernicus Data Space Ecosystem
Geographic Area: Global Coverage
Data Type: Raster (10-meter)
Date Published/Updated and Update Frequency: Data availability for 2020 - 2024
Link/Description:
Sentinel-2 is a satellite product that supports monitoring of vegetation, soil and water cover, as well as the observation of inland waterways and coastal areas. Its primary use in wetland mapping would be for use in machine learning to map potential wetlands based on spectral signatures. There are several products:

- Sentinel 2 Data
- Sentinel 2 Mosaics: Sentinel-2 Quarterly Mosaics are mosaics generated from three months of Sentinel-2 level 2A. The mosaics have four bands of data (Red (B04), Green (B03), Blue (B02) and wide band Near Infrared (B08)). First, cloud masking based on the scene classification layer of the Sentinel-2 level 2 algorithm was applied, then for each pixel and band, within three-month time periods, the first quartile of the distribution of the pixel values was taken as the output value to filter out any bright pixels misclassified as not clouds. If there are no valid pixels for the given timeframe, the pixel is left empty. Jan 2022 to Present. The Most useful layers for wetland mapping: True Color Cloudless and NDVI.
- Sentinel 2 L1C: Sentinel-2 Level 1C products are available globally from 2015 onwards. These products are resampled with a constant Ground Sampling Distance (GSD) of 10, 20 and 60 m, depending on the native resolution of the different spectral bands. Pixel coordinates refer to the upper left corner of the pixel. The Level-1C product provides Top Of Atmosphere (TOA) reflectance images, derived for associated Level-1B products. The most useful layers for wetland mapping: True Color and NDVI.

Description:
The Copernicus Sentinel-2 mission consists of two polar-orbiting satellites that are positioned in the same sun-synchronous orbit, with a phase difference of 180°. It aims to monitor changes in land surface conditions. The satellites have a wide swath width (290 km) and a high revisit time. This capability will support monitoring of changes on the Earth's surface. Sentinel-2 is equipped with an optical instrument payload that samples 13 spectral bands, including four bands at 10 m, six bands at 20 m, and three bands at 60 m spatial resolution.

Recommended Approach

Of the three categories of wetland mapping methods explored, an overlay analysis using wetland indicator data layers is currently the most feasible for the Town of Bluffton based on the available data and time for the analysis. Heads-up digitizing would involve a manual approach to wetland identification by an image analyst that would require more time than either an overlay analysis or machine learning. While machine learning would likely provide more accurate results due to the utilization of high-resolution data and ability to identify complex relationships, it would require ground truth data to use as part of model training and testing. Many of the machine learning examples investigated used the NWI for their training and testing data. Given the limitations of the NWI with regards to age of the data and not mapping smaller wetlands, field delineation of wetlands would be better to use for definitive wetland identification.

The Town of Bluffton does have wetlands delineated for permitted projects that can be used for ground truth data. However, the wetland delineations are currently only available on plan sets in PDF format, which require georeferencing and digitization into geospatial format. The process of digitizing wetlands from all plan sets across the Town would be time intensive. As a starting point, we suggest delineating wetlands from a subset of the available plans to help inform the use of indicators in the overlay analysis, as further described in the overlay analysis section below. The Town can continue to expand the digitized wetland layer with the goal of conducting a machine learning approach in the future to further refine the results.

Overlay Analysis to Identify Potential Wetlands in the Town of Bluffton

In this task, we conducted an overlay analysis to classify the likelihood of wetland presence throughout the Town of Bluffton. Categories of wetland potential were developed using four wetland indicator layers and a Classification and Regression Tree (CART) based on these data layers as described in the Methods section below.

Methods

The method was completed in five steps, including: 1) develop mapping layers of wetland indicators, 2) create a delineated wetlands layer from permitted plan sets, 3) union all layers to create a data table identifying wetland presence and wetland indicators, 4) conduct a CART analysis to categorize wetland potential based on wetland indicators, and 5) create a map of wetland potential. All GIS analyses were conducted in ArcGIS Pro Version 3.5.2 using the NAD 1983 (2011) StatePlane South Carolina FIPS 3900 (Intl Feet) coordinate system to align with the coordinate system used for GIS data in other recent Town studies. CART analysis was conducted using the RStudio package.

Step 1. Develop mapping layers of wetland Indicators

Overlay analysis studies found that too many indicator layers reduced accuracy, and it is better to narrow down to a few of the most representative layers as opposed to overlaying all potential indicator layers. After reviewing available mapping data, along with a literature review of reliable wetlands predictors, we identified four predictors that are both available in the Town of Bluffton and are demonstrated predictors of wetland presence. These included the National Wetlands Inventory (NWI) wetlands layer, the Wetness Index based on Landscape position and Topography (WILT), presence of Hydric Soils and presence of depressions.

- National Wetland Inventory – Wetland presence from the NWI was commonly used as an indicator layer in the overlay analysis studies reviewed. Although the data is based on imagery from 2006 and 2011, it still is an authoritative wetlands source that provides a high likelihood of wetland presence. The NWI data was filtered to wetland types of estuarine and marine wetlands, freshwater emergent wetlands, and freshwater forested/shrub wetlands. Freshwater lakes, ponds, and rivers, as well as deepwater areas that are not wetlands were excluded. Other mapped wetland sources evaluated included the GAP/LANDFIRE National Terrestrial Ecosystems and C-CAP land cover data. However, many areas overlapped with those already identified by the NWI and their resolution of 30-meters limits the ability to detect smaller wetlands, so they were not included in the analysis.

- Hydric Soils – Hydric soils are another commonly used indicator in overlay analysis studies. Areas within the Town with soil rated hydric were extracted from the SSURGO database. Depth to groundwater from the SSURGO data was also investigated but was not incorporated as a separate indicator layer since it is utilized as part of the wetness index described below.

- Depressions – Depressions (also known as sinks) in the terrain are lower than all other neighboring terrain cells (or contours) and are often indicative of wetland locations. The DEM provided by the Town of Bluffton based on the 2020 USGS Savannah Pee Dee SC lidar was resampled from 2ft to 10ft to help minimize noise in the data due to the high resolution and reduce excessive processing time. Arc Hydro[5] tools were then used to identify depressions following the contour tree method in Arc Hydro's documentation for Identifying and Managing Sinks[6].

- Wetness Index – The topographic wetness index (TWI) is calculated from upslope contributing area and slope and is commonly used to model landscape characteristics responsiveness to wetness and provide an indication of locations where wetlands are likely to occur. However, in the coastal plain where groundwater flow dominates the hydrology of low-slope landscapes, the TWI assumptions do not perform as well. A modified Wetness Index based on Landscape position and Topography (WILT) proposed by Meles et al. (2019) was used to account for the unique conditions of the coastal plain that inversely weights the upslope contributing drainage area by the distance to the nearest surface water feature and the depth to groundwater. Contributing drainage area was calculating following terrain preprocessing workflows[7] in Arc Hydro using the resampled 10ft DEM from the depression analysis. Slope was also calculated from the DEM. Groundwater depth was obtained from the SSURGO database. Surface water features from which distance was calculated include water bodies from the 3DEP and C-CAP regional land cover data, as well as streamlines used to produce the SC StreamStats 2018 release[8]. These streamlines were utilized instead of 3DEP flowlines because they were generated from higher resolution topography data than 3DEP and more accurately aligned with channel locations in the DEM based on visual inspection. A WILT value of 7.349 or greater was determined to be the threshold for areas of high wetness potential based on Jenks natural breaks, a histogram review of the WILT results, and visual comparison to digitized wetlands.

$$WILT = \ln\left(\frac{A}{\Delta X * \Delta Z * \tan\beta}\right)$$

Where:
  - A = Upslope contributing drainage area
  - ΔX = Horizontal distance from the nearest surface water feature
  - ΔZ = Depth to groundwater
  - B = Slope in radians

STEP 2. CREATE A DELINEATED WETLANDS LAYER

PDF plan sets provided by the Town of Bluffton were used to identify locations of known wetland from permitted projects and included the following file names:

- Bluffton Park Wetlands Plat (Bluffton Park)
- Harristeeter (Buckwalter)
- 019117 – USACE JD Wetland Letter (Resubmittal) 5.15.24 (Buckwalter)
- 13-5907 Wetland Permit (New Riverside)
- 019033 Wetland Permit (Preliminary) 03 11 24 (Palmetto Bluff Phase 2)
- 016977 Wetland Permit (Preliminary) 7-18-22 (Palmetto Bluff Phase 2)
- 019391 - Wetland Letter (Preliminary) 10.10.24 (Palmetto Bluff Phase 2)

[5] https://www.esri.com/en-us/industries/water-resources/arc-hydro/downloads
[6] https://www.esri.com/content/dam/esrisites/en-us/media/technical-papers/arc-hydro-identifying-and-managing-sinks.pdf
[7] https://www.esri.com/content/dam/esrisites/en-us/media/technical-papers/arc-hydro-overview-of-terrain-preprocessing-workflows.pdf
[8] https://www.sciencebase.gov/catalog/item/5cf01a85e4b0b51330e22aa6

Plans sheets for Bluffton Park, Buckwalter, and New Riverside were extracted from the PDFs and georeferenced using identifiable features within the plan and available GIS data, including parcel boundaries and road intersections. All wetlands and related features were digitized and saved as a feature class along with the types of wetland features (preserved wetland, filled wetland, wetland buffer, etc.). For Palmetto Bluff Phase 2, the Town provided a previously developed polyline layer of wetlands, which we converted to a polygon feature class. We then reviewed the corresponding plan sheets to verify the wetland extents and assign the type of wetland feature.

For the purpose of this analysis, the wetlands were filtered to only those that were noted as preserved on the plan sheets. Wetlands noted as filled on the plan sheets were also included if they were in areas not yet developed based on visual inspection of the Town's 2024 aerial. Areas noted as wetland buffers or filled/cleared wetlands that are currently developed were excluded from the analysis. However, these areas are still included in the digitized wetlands feature class so that they can be utilized by the Town for future studies if needed.

In addition to wetlands, areas confirmed as not wetlands were needed for the CART analysis. We identified these areas by digitizing the project area extent represented on the PDF plan sheets and then subtracting the wetlands so that any remaining areas included those that had not been delineated as wetlands as part of project permitting.

STEP 3. UNION ALL LAYERS TO CREATE A DATA TABLE FOR THE WETLAND PRESENCE ANALYSIS

In this step, we unioned the GIS layers created in steps 1 and 2 to create a dataset for this analysis. The data elements are summarized in Table 4, and the complete data set is included as Attachment A. ("Indicator_Analysis_Digitized_Wetlands_with_Size.csv").

Table 4. Data from union of GIS layers used in the potential wetland analysis

Data Field[1,2,3]	**Information**
Category	Area defined as "Wetland" or "Not a Wetland"
NWI	Inclusion in the NWI layer (yes/no)
Hydric	Presence of Hydric Soils (yes/no)
WILT	Presence or absence of a high WILT value. (yes/no)
Depression	Presence or absence of a topographic depression (yes/no)
Shape_Area	Area of the intersected shape (sf)
WETLAND_TYPE	Wetland_Type identified in the NWI (e.g., "Freshwater Emergent Wetland")
Planset	Name of the planset where the wetland delineations occurred (e.g., "New Riverside")
Total_Wetland_Area_SqFt	Size of the delineated wetland in square feet

1: Information in shaded cells was ultimately not used in the analysis but were evaluated as potential model elements.
2: Shape Length was also included in the dataset but was not evaluated or included in any analysis.
3: The data was slightly modified to convert the "X" for presence of a factor to "Yes/No" prior to analysis.

Step 4. Use CART Analysis to categorize wetland potential based on wetland Indicators

In this step, the data summarized in Table 4 were used to develop a screening tool to identify wetland potential. The analysis used the RStudio package "Rpart" (Therneau et al., 2025), with the following elements for the chosen model.

- The equation used was:
  Category ~ NWI+WILT+Hydric+Depression

- The model was weighted by shape area, so that larger shapes more heavily influenced the model results than smaller shapes. This weighting was chosen to ensure that very small "sliver" shapes did not have an undue influence, and to better reflect the total area affected by each shape. Early trials that did not weight by area resulted in undue influence of very small area geometries.

- Since the model will be used as a screening tool, the team judged that the model should err in the direction of "overclassifying" versus "underclassifying" wetlands areas, with the argument that these false positives could then be identified with field verification. To achieve this goal, the model incorporated a Loss Matrix (Table 5) that incorporated greater penalties for missing a wetland (false negative) than for falsely identifying a wetland (false positive). The resulting decision tree is intentionally biased toward classifying land as wetlands.

Table 5. Loss matrix used in the wetland potential model

Actual/Predicted	Wetland	Not a Wetland
Wetland	0	5
Not a Wetland	1	0

- The underlying model controls were modified using rpart.control function. Modifications included lowering the model complexity (cp) value to 0.001 from 0.01, and changing the minisplit value from 20 to 10, and setting the minibucket value to 5. These modifications enabled the model to capture finer distinctions between categories.

The resulting model, described in more detail in the "Results" section below, was interpreted based on the modeled percent chance of an area being a wetland (Table 6).

Table 6. Categories Used to Interpret Model Results

Wetland Potential (% of area)	**Category**
<20%	Low
20%-50%	Medium
>50%	High

The categorization tree resulting from the model was plotted using the package rpart.plot (Milborrow, 2025).

Step 5. Create a map of wetland potential

The union of the wetland indicator layers was then assigned a low, medium, or high wetland potential based on the combination of wetland indicators and the corresponding wetland potential classification in Table 7.

Results

The resulting classification is presented in Table 7. In a very small area (4% of the total plan area evaluated in cases where NWI wetlands have no other wetland indicators), NWI wetlands would be classified as "Not a wetland". In general, though, the CART method has the effect of capturing wetland areas that are not included in the NWI wetland area. This effect can also be seen in the accompanying wetland map, where the Medium and High potential wetland areas expand beyond the area covered by the NWI.

Table 7. Classification based on mapped predictors

Presence of Mapped Wetland Predictors				Wetland Probability	Wetland Potential Class	Determination for Screening
Hydric	Depression	WILT	NWI			
No	No	No	No	4%	Low	Not a Wetland
Yes	No	No	No	8%	Low	Not a Wetland
No	Yes	No	No	4%	Low	Not a Wetland
No	No	Yes	No	4%	Low	Not a Wetland
No	No	No	Yes	15%	Low	Not a Wetland
Yes	Yes	No	No	29%	Medium	Wetland
Yes	No	Yes	No	27%	Medium	Wetland
Yes	No	No	Yes	37%	Medium	Wetland
No	Yes	Yes	No	4%	Low	Not a Wetland
No	Yes	No	Yes	38%	Medium	Wetland
No	No	Yes	Yes	74%	High	Wetland
Yes	Yes	Yes	No	27%	Medium	Wetland
Yes	Yes	No	Yes	37%	Medium	Wetland
Yes	No	Yes	Yes	74%	High	Wetland
No	Yes	Yes	Yes	74%	High	Wetland
Yes	Yes	Yes	Yes	74%	High	Wetland

When comparing the relative performance of the CART technique with using NWI mapped wetlands alone (Table 8), it appears that the CART technique performs better using the producer's accuracy measure, particularly for small wetlands. Overall, the CART method identified 82% of digitized wetlands compared with 69% using NWI only. For small (<1 acre) wetlands, these numbers are 62% and 35%, respectively. The user's accuracy, by contrast, is slightly lower when using the CART method for wetlands as a whole, and much lower for small wetlands compared to the NWI. Among all mapped wetlands using the CART technique, 50% of the mapped area is within a digitized wetland, compared with 55% of NWI mapped wetlands. For small (<1 acre) mapped wetland areas, the accuracy is 20% using the CART Mapping compared with 58% for the NWI only. One reason for the lower user's accuracy is due to the CART method's greater identification of smaller areas than the NWI. With a greater extent of potential mapped wetlands, there is also greater potential for errors of commission. A second reason is because the analysis was done for the complete extent of the Town, which included areas that have already been developed. Mapped areas of wetland potential within the already developed areas would show an overestimation of potential wetland locations.

Table 8. Performance of the CART technique compared with NWI Only

Performance Metric[1]	Wetland Size[2,3]	Method	
		CART Mapping	NWI Only
Producer's Accuracy	All	82%	69%
	Small	62%	35%
	Large	83%	70%
User's Accuracy	All	50%	55%

	Small	20%	58%
	Large	52%	55%

1: Producer's accuracy refers to the % of actual wetland are captured by each technique. User's accuracy refers to the % of mapped wetland area that is a field-identified wetland. Accuracy is determined using areas classified as Medium and High wetland potential.
2: Small wetlands refer to wetland areas <1 acre.
3: For Producer's Accuracy, the wetland size is the size of field-identified wetlands, while the wetland size for User's accuracy is the size of mapped wetlands.

Figure 1 shows the four indicator layers for a portion of Palmetto Bluff Phase 2 in comparison to delineated wetland extents. The NWI aligns with the larger delineated wetlands but does not overlap with many of the smaller wetlands, as would be expected due to the data limitations outlined in the Data Availability section. Hydric soil covers a large extent of the Town and therefore also overlaps with many of the delineated wetlands. Both the depressions and high WILT overlap with many of the smaller wetlands that are not covered by the NWI.

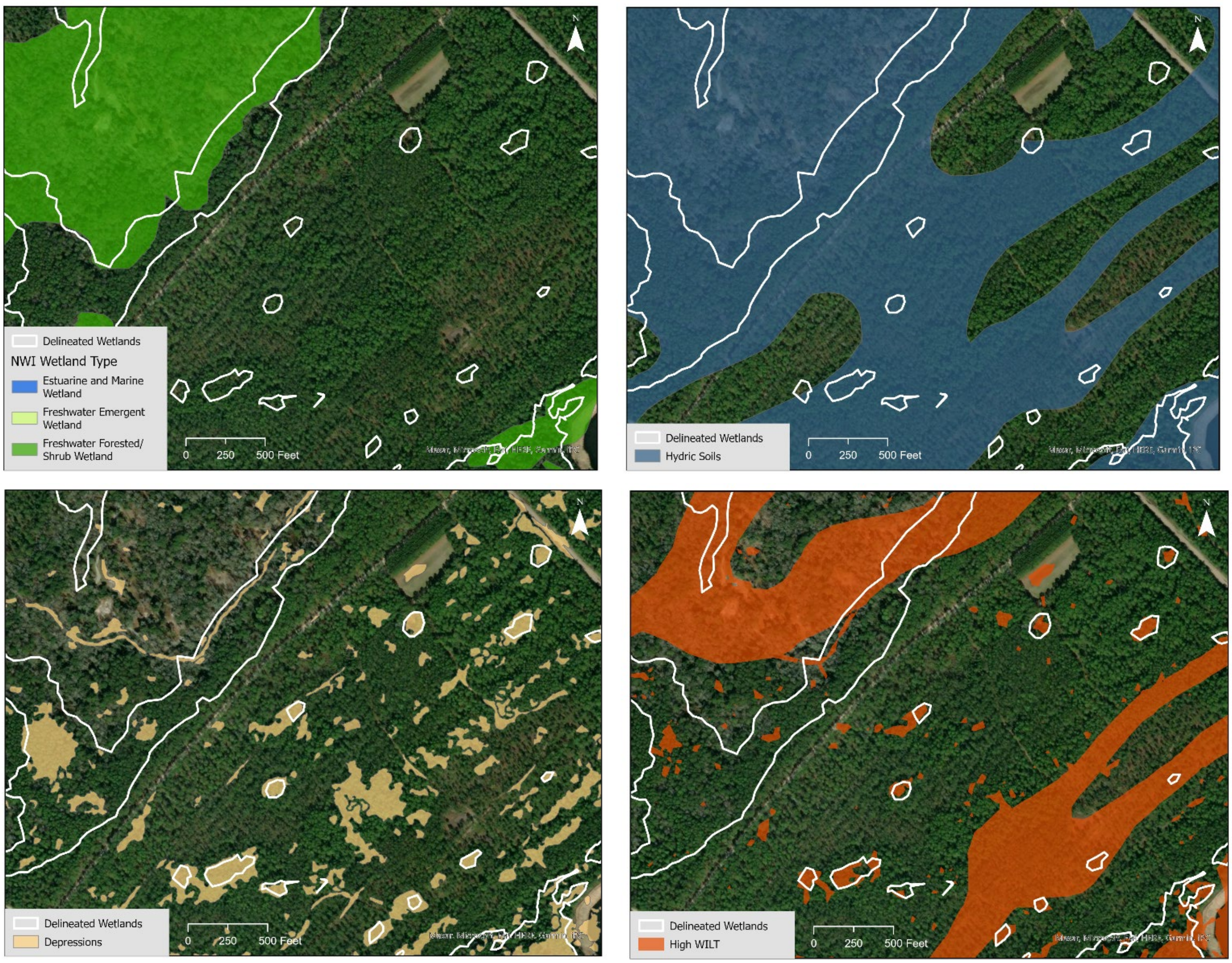

Figure 1. Wetland indicators for delineated wetlands in Palmetto Bluff Phase 2

Figure 2 provides examples of the mapped wetland potential for portions of Palmetto Bluff Phase 2 and New Riverside.

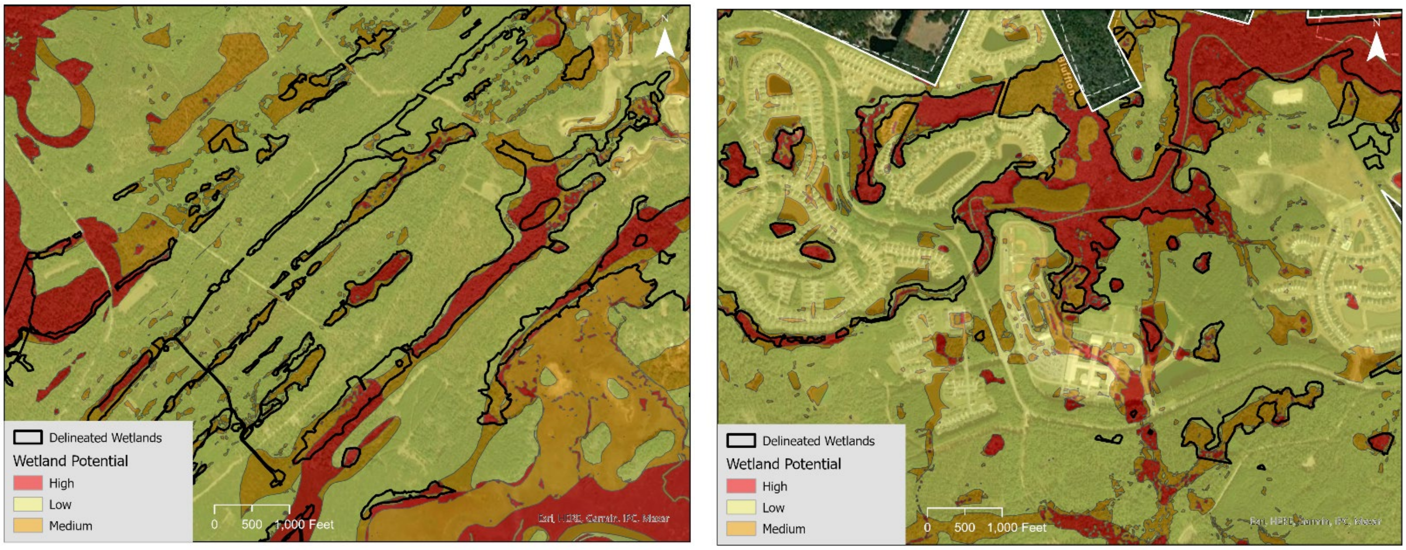

Figure 2. Mapped wetland potential for Palmetto Bluff Phase 2 (left) and New Riverside (right)

NEXT STEPS

The Town can use the resulting map of "potential wetlands" to assist with the implementation of Section 5.10.7 of the Unified Development Ordinance (UDO). Anyone proposing to carry out land development within a wetland or wetland buffer area is subject to these provisions. While field delineation of wetland boundaries by a professional will be the ultimate determinant of where wetland and wetland buffers boundaries are located, the existence of an updated Town map of wetlands and potential wetlands allows both the Town and the applicant to know in advance of conducting a natural resources inventory which areas of the site are likely to have wetlands present and plan accordingly. The UDO can be revised to refer to the Town's updated map. For example, Section 5.10.7.A may be reworded to "This Section shall apply to all Land Development within a wetland, potential wetland, or wetland buffer area, except as otherwise set forth herein." Similarly, exceptions to the wetland delineation requirement in Section 5.10.7.B could be modified to state that a wetland delineation shall not be required if the following conditions are met…"no Wetlands or Potential Wetlands are identified on the site by any prior Wetland Delineations, or any existing watershed plans or Advanced Identification of Disposal Areas (ADID) studies, interim watershed plans, National Resources Conservation Service (NRCS) wetland inventory maps, or United States Fish and Wildlife Service National Wetlands Inventory Maps; or Town wetland maps."

For future advancements to the map of potential wetlands, the Town can continue to expand the digitized wetland GIS layer by adding in wetlands from additional plan sets from areas that have already been developed and/or require that future permitted projects provide wetland delineations in GIS format for ease of incorporation. It is recommended that the delineated wetlands be distributed across the extent of the Town and include a variety of wetland types, in particular the smaller wetlands less than 1 acre that are commonly missed by the NWI. This expanded delineated wetland layer could then be used as a training and testing dataset for a machine learning approach that can help refine the map of potential wetlands by incorporating more advanced analyses utilizing additional sources such as satellite imagery.

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APPENDIX A: DATA FROM UNION OF GIS LAYERS USED IN THE POTENTIAL WETLAND ANALYSIS

Provided as a separate .csv file.